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ScienceDirect
Procedia Engineering 118 (2015) 522 – 529
Procedia Engineering
www.elsevier.com/locate/procedia

International Conference on Sustainable Design, Engineering and Construction

Evaluation of Lighting Performance Risk Using Surrogate Model and EnergyPlus

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Abstract

In building retrofit projects, numerous sources of uncertainty about building performance need to be addressed. Deterministic simulations are usually used to estimate the potential performance difference from a baseline building. This approach needs building model calibration. Varying uncertain building parameters could lead to orders of magnitude simulation times. For example, in a lighting retrofit project, uncertainty (e.g., lamp input wattage, and varying weather conditions may negatively affect model calibration and lighting energy savings, which increases the chance of default on performance contract. Therefore, the aim of this paper is to develop a method that can conduct risk analysis based on building model (e.g., building information modelling). A stochastic occupancy model is used to simulate the occupancy pattern. Two lighting control strategies (occupancy and daylight controls) and two luminaire types (LED and fluorescent) are considered. Historical weather data is analyzed using statistical analysis, and the extreme weather conditions are generated to evaluate the impact of weather conditions on the lighting and HVAC energy usage. Then, EnergyPlus is used to simulate the energy usage based on different lamp types, control strategies, occupancy patterns, and weather conditions. A surrogate model is developed by using a small sample size of simulation data to construct an approximation surface to enable fast computing time. This method can evaluate impact of uncertainty of risk factors (e.g., occupancy level, luminaire type, weather) on lighting and HVAC energy usage and lighting electricity demand. This method can also prioritize risk factors based on sensitivity analysis on building performance and help users to choose different lamp types to minimize risks.

Peer-review under responsibility of organizing committee of the International Conference on Sustainable Design, Engineering and Construction 2015

Keywords: Risk analysis; Surrogate model; EnergyPlus; Energy simulation; Neural networks

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Peer-review under responsibility of organizing committee of the International Conference on Sustainable Design, Engineering and Construction 2015
doi:10.1016/j.proeng.2015.08.471

1. Introduction

Dynamic simulation models are constructed in a retrofit decision process to benchmark the performance of existing buildings and predict the effect of retrofit interventions [1]. Uncertainty and sensitivity analysis of building performance has been investigated in building design and retrofits. Professionals have to conduct sensitivity analysis to quantify the influence of risk parameters on the building performance and financial outcomes [2, 3]. To do this, a distribution is chosen for a number of input parameters and numerous simulation models are generated and simulated to determine the statistics of important outputs.

Problems arise when it comes to simulation time and input parameter sampling. EnergyPlus has been extensively used for energy simulation [4], and Radiance and Daysim have been used for lighting simulation [5, 6]. Sensitivity analysis in building performance analysis [2] requires a large number of simulations [6, 7]. It can take a prohibitively long time to run exhaustive simulations. For example, Shen et al. studied lighting control strategies under different parameters i.e., climate zones, blinds (interior, exterior) and window-to-wall ratios. The number of simulations significantly increases when more options of parameters are evaluated and combined together [8, 9]. Simulation methods with faster runtime algorithms were proposed to address the long runtime of energy simulations. One solution is to develop new models that have less runtime. For example, Hu and Olbina [10] developed an analytical model to simulate the daylighting performance of blinds with blind reflectance and glazing transmittance. A neural network model was also developed to predict the illuminance and building energy [11, 12]. Another solution is to reduce the number of simulation models evaluated, but this comes at the expense of limiting parameters or ranges of parameters Thus, developing a surrogate model as a substitute for time-intensive energy simulations is valuable as an alternative approach to this problem. It treats the computationally expensive simulation code as a black-box to generate data and uses adaptive sampling techniques to reduce the sample points. Once the surrogate model is developed, the input variables can be directly fed into the surrogate model to generate the output values (i.e., energy consumption) very quickly without repeating the simulation process.

Some building parameters are usually ignored or inappropriately selected during sensitivity analysis. For example, a weather file usually defines a number of variables with a large amount of data, yet typically only a single scalar variable such as temperature is permuted during the sensitivity analysis [13]. Another parameter that is typically ignored is lighting control strategy. Different control strategies significantly affect building energy, especially lighting energy usage. Significant savings can be achieved on lighting energy usage using integrated closed-loop blind and lighting control strategies [9]. Therefore, to overcome the problems, this research is aimed to develop a method to evaluate the influence of different risk factors (e.g., weather condition) on the building performance such as HVAC/lighting energy usage, and electricity demand for lighting for lighting retrofit projects. The method uses surrogate model to reduce simulation time.

2. Methods

The overall method is shown in Fig. 1. The first step is sampling data using techniques such as Latin hypercube sampling. The sampled input variables (i.e., risk factors in a lighting retrofit project) include occupancy level, weather condition, control strategy, and lamp type. In the surrogate model, the sampling position in the current iteration is determined by the previous position. For example, in Fig. 2, in the first iteration, the prediction curve of the surrogate model has a large deviation from simulation results at position A even though values at the sample points (black dots in the figure) have a very small error. Through adaptive sampling in surrogate model, in the next iteration, a new sample point is added at the position A where a maximum error occurs. Through this process new sample points are gradually added into the model at selective positions.

The sampled risk factors are added into the EnergyPlus input file. The output of energy simulation includes energy consumption, electricity demand, etc. In the next step, a surrogate model is generated, typically using models based on polynomial response surfaces, Kriging, support vector machines, or neural networks. A preliminary test using a DOE reference building for medium-sized office located in Chicago was conducted to select the optimum model. The results show that neural networks generally provide good results compared to polynomial response surfaces, Kriging and support vector machines. These results are also consistent with the previous study using neural networks to predict energy consumption [14]. Once the surrogate model is generated, the input variables are sampled in the whole variable space, and a large number of combination of the input variables are fed into the surrogate model to produce probability distributions for lighting and HVAC energy consumption.

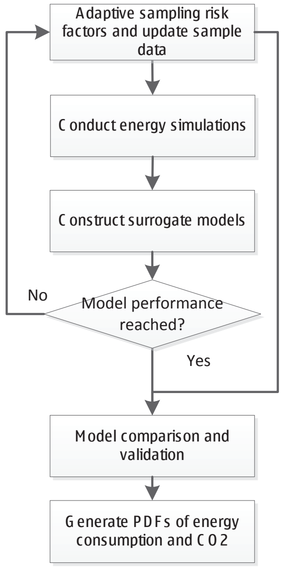


Fig. 1 Model structure

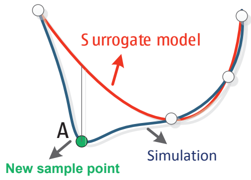


Fig. 2 Illustration of adaptive sampling technique

The risk factors considered in this method include occupancy level, weather condition, lamp type, and control strategy. In lighting retrofits, the need is to analyse the energy performance risk involved when a fluorescent lamp (e.g., T12 or T8) is replaced by another lamp (usually LED). Occupancy pattern is defined automatically (using occupancy model) or manually (e.g., onsite survey and audit). We developed a stochastic occupancy model using actual office data to simulate the occupancy status in the building [9]. In this dynamic occupancy model, each individual occupancy state is represented as a Markov Chain where the state transition probabilities are derived from the actual occupancy data.

The retrofit buildings usually use manual control or simple schedule based control of lighting. The new control strategy may be occupancy based control, or occupancy + daylighting control. The manual control or schedule based control controls lighting on/off based on a pre-defined schedule. The occupancy control strategy controls the on/off status of the lighting based on the actual occupancy status. The occupancy and daylighting control combines the occupancy information and daylight control. Lights are dimmed up or down based on the daylight levels in perimeter zones.

The weather condition affects the HVAC and lighting energy consumption when daylight control is used. TMY weather files are typically used in energy and lighting simulations. We developed a method to simulate extreme weather conditions based on statistical analysis using historical weather data. The generated extreme weather file can be used for energy simulation. The method is based on the Sandia method [15], which is an empirical approach that selects individual months from different years of the period of record to formulate a TMY weather file.

The method is shown in Fig 3. The historical weather data can be retrieved from a database. A typical data source is the NREL database which contains TMY2 and TMY3 historical weather files for more than 20 years. In order to identify extreme weather conditions, statistical differences between historical data and typical data were quantified according to the Sandia method by calculating Finkelstein-Schafer (FS) statistics for relevant weather data. FS is defined in the following equation: FS = $(1/n)\sum_{i=1}^{n}\delta_i$, where δ_i = absolute difference between the long-term CDF (cumulative distribution function) and the candidate month CDF at x_i, and n = the number of daily readings in a month. The weather variables evaluated include dew and dry bulb temperature, wind speed, global radiation and direct radiation. Based on the calculated statistics, the extreme weather is selected based on the CDF difference. For example, assume weather variables in January of 1995 has the largest CDF difference compared to the CDF of TMY data. Then this month data is selected as extreme cloudy year data for January. Time periods other than monthly may also be used. For example, the time period may be a week instead of a month. In the next step, the weather data calculated for each time period (e.g., month, week) is combined in order to define a whole year representing the extreme condition.

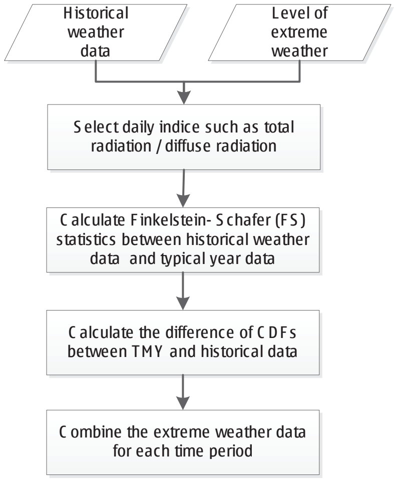


Fig 3 Flow chart of generating extreme weather data from historical weather data

3. Case Study

3.1. Simulation settings

The US DOE commercial reference building model for medium office is chosen as the retrofit building for this case study [16]. The building model for Chicago, IL is selected. The building has three floors and each floor has four perimeter zones and one core zone (see Fig. 4). The building envelope thermal properties comply with ASHRAE Standard 90.1-1989. The exterior wall is set to steel frame walls. Packaged multi-zone variable air volume with plenum zones, gas furnace, and electric reheat are used. For the electric lighting, the mean wattage per square meters for LED is set to 11.52 w/m^2 and for T12 it is set to 13.83 W/m^2.

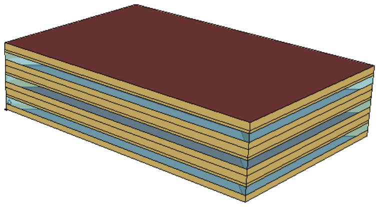


Fig. 4 Reference building model

We used the SUrrogate MOdeling (SUMO) Toolbox, which is a Matlab toolbox that automatically builds accurate surrogate models based on a given data source within the accuracy and time constraints [17]. The toolbox minimizes the number of data points (which it chooses automatically as adaptively and autonomously as possible) since they are computationally expensive to generate. The neural network model is used as the surrogate model.

The risk factors are simulated using the following sampling techniques.

- Weather condition: three levels of weather and sky condition are generated: overcast (< 30%), medium (30-70%), and clear (> 70%). Gaussian distribution is used for each level. The standard deviation set to 20%. For example, when the sampled probability is 25%, then the sky condition is set to overcast. In each sample data, the weather file generator will generate the corresponding weather file based on the probability value..
- LED input wattage: the mean wattage is set to 11.52 W/m^2 for LED and 13.83 W/m^2 for T12 lamp; Gaussian distribution is used with a standard deviation of 0.5 W/ m^2.
- Occupancy level: the occupancy level is split to three levels: medium (e.g., mean peak occupancy level = 50% with a standard deviation of 10%), low (e.g., mean peak occupancy level = 30% with a standard deviation of 10%) or high (e.g., mean peak occupancy level = 80% with a standard deviation of 10%). Gaussian distribution is used for each level. For example, Fig. 5 shows the occupancy pattern in an open plan office with a peak level = 90%.

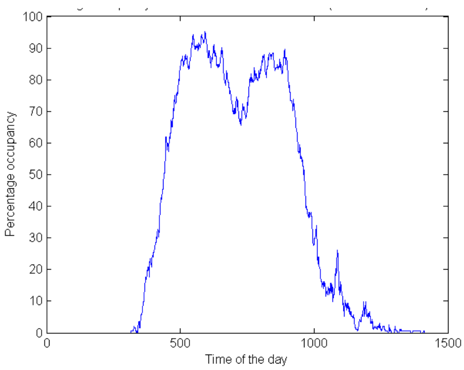


Fig. 5 An example of occupancy pattern with occupancy peak level = 90%

4. Simulation results

The training and testing results of the neural network model for predicting lighting energy consumption is shown in Fig. 6. The results indicate that the model has a very good performance. It can accurately predict the lighting energy consumption. The results are consistent with the previous study that shows that lighting energy shows a linear relationship with many building parameters [18]. The plots in the figures represent the results using occupancy + daylight control. After generating the model, users can predict the probability distribution. For example, the distribution of the difference between LED and T12 lamp energy usage is calculated (see Fig. 7). The occupancy level and weather condition are set to M (medium). The average occupancy level is about 50% with a standard deviation of 10%. The weather condition is set to M (medium) which indicates the weather clearness is in the range of 40% to 60% within the past 20 years. The standard deviation of input wattage is set to 0.5W/m^2. The results also show that using occupancy + daylight control has less risk for the lighting retrofit project. The minimum lighting energy savings by replacing T12 with LED is more than 170 kWh per year.

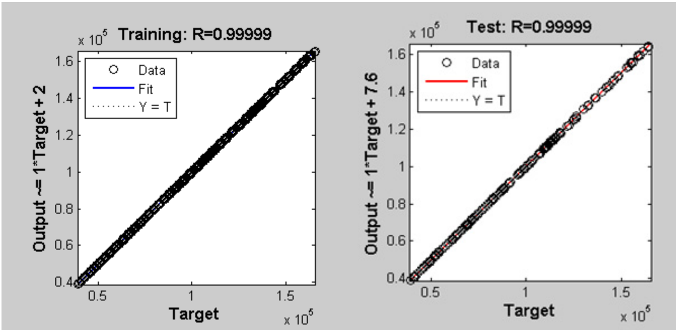


Fig. 6 Neural network training and testing results for lighting energy consumption

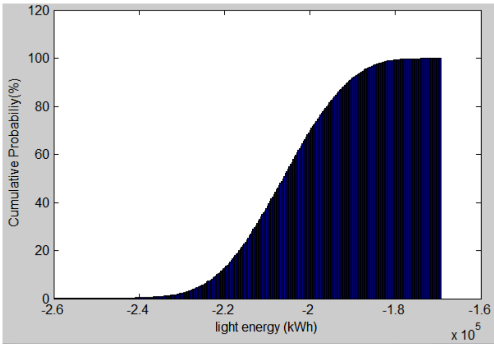


Fig. 7 CDFs of lighting energy difference between LED replacement and T12 (occupancy + daylight control)

HVAC energy consumption is also predicted by the neural network model. In general, the model has good performance with R = 0.97-0.98 (see Fig. 8). In the plots of the probability distribution (see Fig. 9), the occupancy level and weather condition are set to M (medium). Occupancy + daylight control strategy is used for LED lamp. The standard deviation of input wattage is set to 0.5W/m^2. There is lower risk and lower energy consumption when using occupancy based control and a higher energy consumption when using occupancy + daylight control. This is the opposite case when compared to lighting energy consumption.

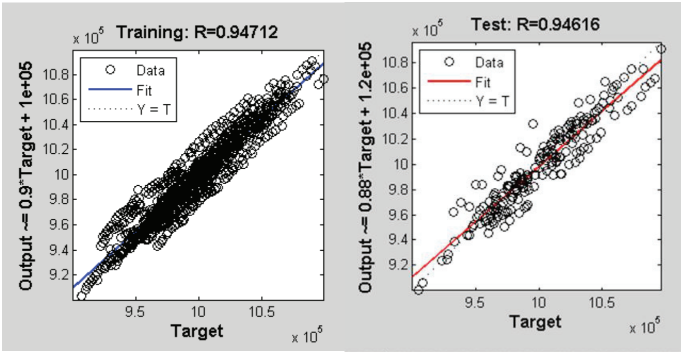


Fig. 8 Neural network training and testing results for HVAC energy consumption

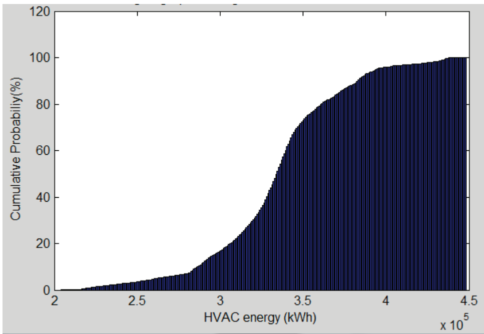


Fig. 9 CDFs of HVAC energy difference between LED replacement and T12 (occupancy + daylight control)

An advantage of using LED is to reduce the electricity demand charge, which can be predicted using neural networks. The model performs well in general (see Fig. 10). Fig. 11 shows the distribution of electricity demand when the occupancy level and weather condition are set to medium. Comparing CDF of the LED under occupancy + daylight control to T12 shows that using LED results in a lower electric demand. The electricity demand for both LED and T12 lamps is about 470 kW under probability of 80%. However, the electricity demand using T12 shows a long right tail, resulting in 470 kW – 950kW electricity demand with a probability of 20%.

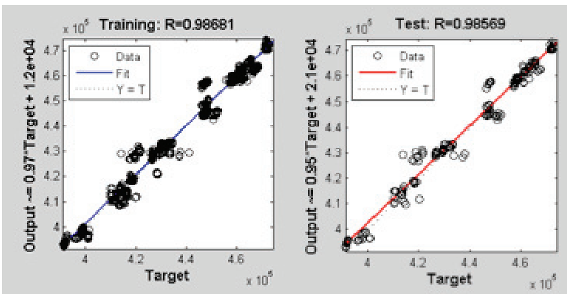
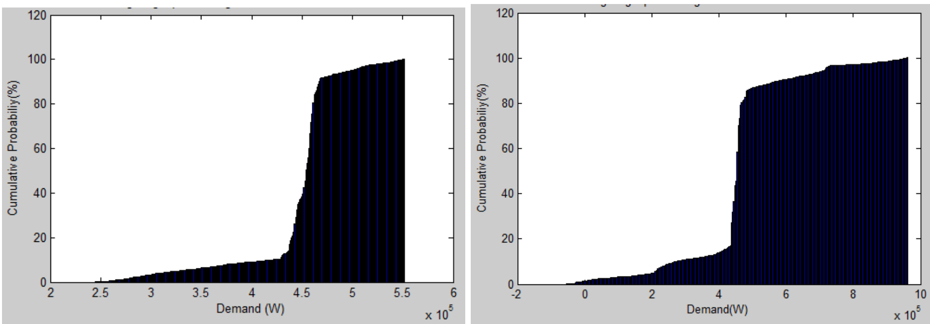


Fig. 10 Neural network training and testing results for HVAC energy consumption



(a) LED (occupancy+daylight) (b) T12 (no control)

Fig. 11. CDFs of lighting demand difference between LED replacement and T12

5. Conclusions

Building retrofits can benefit from simulation-based studies that benchmark the performance of existing buildings and predict the effect of retrofit interventions. To evaluate risks a large number of simulations have to be done, resulting in significant time increase. In this research, we developed a method that uses a surrogate model to predict the lighting and HVAC energy consumption and lighting electricity demand under different risk parameters such as control strategy, lamp type, weather, and occupancy. The surrogate model uses an adaptive sampling technique for variable sampling in order to reduce the number of data points sampled. The probability distributions of risk factors are generated using the sampling methods in surrogate model. A case study is presented to test the method using a commercial reference office building. The method can predict the energy consumption accurately and can also generate probability distributions to quantify potential risks that might impact the performance contract in a lighting retrofit project.

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